Topic: Probabilistic Forecasting of Long-Term Green Hydrogen Resilience via Stochastic Climate Modeling and Data Assimilation

Abstract The reliability of Green Hydrogen production is fundamentally constrained by the intermittency of renewable energy. Current feasibility studies often rely on static historical weather data, which fails to account for the non-stationary nature of the climate system. As climate change alters atmospheric dynamics, the probability of "Energy Droughts" (extended periods of low wind and solar) is shifting. This research proposes a Probabilistic Forecasting framework to quantify these future risks. Instead of predicting a single deterministic future, we will model the regional atmosphere as a Stochastic Dynamical System. By applying Data Assimilation and a simple Machine Learning model to fuse global climate projections with local observations, we aim to rigorously estimate how the likelihood of supply failure evolves over the coming decades.

Methodology The approach integrates advanced probabilistic concepts with practical machine learning to assess climate risk:

Stochastic Modeling and Ensembles: Rather than assuming a fixed weather pattern, we will treat the local climate as a system driven by both predictable trends and random noise. To quantify the uncertainty of future energy droughts, we will employ Ensemble Prediction. This involves generating many possible future climate trajectories (Monte Carlo samples) to map out the full range of risks, specifically focusing on extreme low-energy events rather than just average conditions.

Data Assimilation and Machine Learning: Global Climate Models (CMIP6) are physically robust but too coarse for local planning. To bridge this gap, we will use Data Assimilation concepts. We will implement a simple Machine Learning model (such as a Random Forest or Regression Tree) to act as the "observation operator". This model will learn the statistical relationship between coarse global atmospheric patterns and precise local weather data (ERA5). By "assimilating" the global projections through this ML model, we can downscale the data to generate high-fidelity local forecasts for the year 2050.

Risk Attribution via Bayesian Inference: Finally, we will apply Bayesian Inference to track how the probability of an energy drought changes over time. By treating the risk as a probability distribution that updates as we analyze different future decades (updating the "posterior"), we can statistically distinguish whether a forecasted shortage is just normal weather variability or a genuine shift caused by climate change.

References

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